ASSESSING MUSCULOSKELETAL ABNORMALITIES WITH DEEP LEARNING

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ABSTRACT

Introduction: Musculoskeletal disease is one of the leading global causes of disabilities and lower retirement age. Researchers and health institutions are attempting to solve the problem by improving technology within the medical field to find better ways to aid patients. One of the most impactful innovations is the usage of artificial intelligence, specifically the neural network model.
Purpose: This article aims to evaluate current artificial intelligence-based approaches which are presented as the solution to tackle difficulties regarding musculoskeletal condition prevention and diagnosis.
Method: This article is a literature review researched using derived qualitative research using available research materials. Sources are selected from publications where researchers propose new neural network models used in deep learning which are relevant to current health problems.
Result: The currently tested clinical applications include magnetic resonance imaging (MRI) image reconstruction, joint localization, level of severity determination, knee osteoarthritis prediction, arthritis distinction, and disease-specific joint regions identification.
Conclusion: Artificial intelligence in the medical field aids early prevention and diagnosis by improving efficiency, imaging quality, and diagnosis accuracy. Integrating a multidisciplinary approach is crucial to develop a precise patient-centric intervention system.

Keyword: musculoskeletal; artificial intelligence; deep learning; literature review; neural network

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INTRODUCTION

The human body's musculoskeletal system provides structural support and stabilization, facilitates movement, stores energy, produces blood cells, and stores minerals.[8] Therefore, abnormalities in the musculoskeletal system may impair mobility and dexterity, leading to disabilities and lowering retirement age globally. Clinical problems may affect the spine, bones, joints, muscles, and multiple systems due to their clinical manifestation. By 2021, 1.71 billion people will have been affected by the conditions, with lower back pain symptoms compromising 568 million cases.[2] Various organizations and health institutions have been working to solve this problem, with the primary focus of establishing the global rehabilitation agenda.[10] Physicians and scientists are also continuously improving technology within the medical field to find better ways to aid patients' musculoskeletal diseases. One of the most impactful technological innovations in recent years is the invention of artificial intelligence.

Artificial intelligence is the field of computer science that simulates human intelligence on machines to accomplish tasks that required natural intelligence. Machine learning refers to artificial intelligence, which can learn based on an algorithm without requiring explicit programming. Consequently, the quality of machine learning improves over time.[3] Conventionally, tasks are performed within four steps: input, feature extraction, machine learning, and output. Feature extractions were done manually and need to be transformed before being used to train a machine learning algorithm. Fortunately, deep learning networks allow automatic feature extraction.[5] Deep learning is a subset of machine learning which combines feature extraction and machine learning steps to allow an automated process done by the neural network.

The artificial neural network (ANN) model presented by deep learning mimics how neurons in the human brain work. The network processes pattern recognition and relationships between information within three layers. First, the input layer presents the information for the model to learn. Then, the information is computed by one or several hidden layers. Finally, the processed information is relayed to be concluded in the output layer. Parallel computations may be performed, and the ANN may demonstrate nonlinear relationships.[9] Convolutional neural network (CNN) works by discerning the spatial characteristic of an image and complementing the information using surrounding objects as references, accurately identifying the object and its location. CNN is commonly used for computational tasks such as classifying images recognizing objects, and segmenting images.[7]

The focus of this review article is the application of deep learning to assess musculoskeletal conditions. This review article discusses four approaches to aid musculoskeletal treatment to evaluate the approach's effectiveness and the current limitations— in disease identification, localization, magnetic resonance imaging (MRI) image reconstruction, and determining the severity of musculoskeletal conditions. The benefit of conducting this research is presenting lesser-known methods and evaluating potential improvement areas. The implication of this review for the field is to show the potential clinical application to direct future research towards further improvements of effective neural network models.

RESEARCH METHOD

This article is a literature review. The methodology is derived from qualitative research, which uses available research materials. The period for the publications selected is within the last five years, from 2018 to 2022.

Research questions and objectives are formulated by considering the use of artificial intelligence in the medical field to aid patients with musculoskeletal diseases.

Sources are identified from recent publications concerning treatments of musculoskeletal problems. The rationale for selecting sources is to choose publications where researchers propose new neural network models used in deep learning which are relevant to the current health problems. Chosen neural network models had been tested on subjects, and the neural networks could possibly be applied for clinical uses in the medical field.

The procedure of analyzing the sources is first to identify the intended use, which is demonstrated in the experiment. Then, the procedure continues by determining how network models extract relevant sample features and evaluating how network models classify information as the assigned output. Afterward, the research is concluded by assessing the effectiveness of the proposed model in the medical field and considering the limitations in the demonstration or areas available for improvement.

RESULT

Four deep learning models were selected and compared based on the clinical application, musculoskeletal compartment, imaging modality, AI-based approach, sample size, and performance. The clinical applications include MRI image reconstruction, joint localization, level of severity determination, knee osteoarthritis prediction, arthritis distinction, and disease-specific joint region identification (table 1)

Table 1. Comparison of the four AI-based approaches based on the purpose musculoskeletal compartment, imaging modality, sample size, and performance.

Clinical Application	Musculoskeletal Compartment	Imaging Modality	AI-based Approach	Sample size	Performance
MRI image reconstruction[1]	Bone, joint, cartilage, meniscus	MRI	3D CNN (DeepResolve)	124 patients (training data sets), 17 patients (test)	Quality diagnostic performance, high-resolution images
Joint localization and level of severity determination[6]	Joint (Hands, wrist, feet)	X-ray	Deep CNN (*Local label smoothing*)	367 patients, four image per patient (training data sets)	Smooth interpolation between classification and regression objective
Knee osteoarthritis prediction[7]	Knee	Nonimage	ANN and CNN (Deep-KOA)	132,594 diagnosed with KOA, 1,068,464 without KOA (control)	Risk prediction with high sensitivity and specificity
Arthritis distinction and disease-specific joint regions identification[4]	Bone, joint	Ultrasound	Neural network (CSAE)	617 patients, 932 scans (data set)	Allows signing and clustering as conditions or healthy control

AN= Artificial neural network, MRI = Magnetic resonance imaging, CNN = Convolutional neural network, KOA = knee osteoarthritis, CSAEE = convolutional supervised auto-encoder

MRI image reconstruction

Knee MRI images were reconstructed using a 3D CNN entitled DeepResolve. This allows two main approaches for reconstruction; downsampling feature and Sparse Coding Super-resolution (ScSR). The feature allows inversing the downsampling factor to generate thick-slices from thin-slice images. ScSR estimates the sparse coefficient of a low-resolution image to construct a high-resolution output.[1]

The network utilizes double echo in steady-state (DESS) to develop an algorithm capable of reconstructing the ground-truth image. Reconstruction is nearly identical, with a slight difference identified at 50x amplification. Additional features on the ground-truth image, such as meniscal and cartilage lesions, are reproduced moderately.

Joint localization and determination of severity level

The Sharp/van der Heijde method (SvH) is an improvement to the Sharp radiograph scoring criteria, which includes assessment for feet and sites in hand, which was previously difficult to observe. According to van der Heijde, 16 areas of erosion and 15 areas of joint space narrowing score for each hand and wrist. Additionally, there are six areas of erosion and 6 areas of joint space narrowing for each foot.[11]

The *local label smoothing* of the CNN model enables feature extraction and information processing to draw a conclusion based on the SvH criteria. First, a segmentation mask is applied by converting joint centers into an object-type annotation. Some pixels are then either assigned as the class related to the joint or an additional background class. The parameters used to sort pixels are r and R, with the condition of r ≤ R. r is the distance to the nearest joint center. Pixels located further than R are considered the background class, while pixels that fall between the range are not associated with any class. Second, the network is trained to meet training objectives, which refers to the joint class in the SvH. Some areas and spaces may overlap, creating points of interest. Therefore, each pixel is assigned to corresponding joint classes and mapped accordingly. Positive pixels are then used to calculate the narrowing score and erosion score. Next, using *local label smoothing,*[6] prediction results are shown as small integers. These predictions are presented as classification rather than constrained regression. Final scores are shown as a weighted average.

Knee osteoarthritis prediction

The risk prediction of knee osteoarthritis (KOA) is approached with binary classification problem-solving. The Deep-KOA model integrates two deep learning networks, the convolutional neural network (CNN) and artificial neural network (ANN), enabling the model to perform computational tasks and model complex nonlinear relationships. Deep-KOA utilizes a nonimage learning source to develop the algorithm known as the electronic medical record (EMR) of patients. EMR matrix data includes the patient's gender, age, etc. Other important features may include diagnostic and medications, where each weekly diagnosis code is divided by 7, and each weekly medication value is divided by 28.

The EMR data usually includes longitudinal information with few predictor variables. Hence, CNN is used to identify the EMR, while static data are presented in ANN. By integrating diagnostics and medication data, the Deep-KOA model can predict the risk of KOA.[7] This is applicable in developing precise prevention programs for patients with a high risk of KOA, which requires high sensitivity and specificity.

Arthritis distinction and disease-specific joint regions identification

Structural patterns of the articular bone shape are distinguished using the convolutional supervised auto-encoder (CSAE) Neural Network to determine whether the condition present is a form of rheumatoid, psoriatic arthritis, or healthy control. The network utilizes the function of heatmap visualization to observe the disease-specific features. When the model is presented with an unidentified arthritis condition, clustering and prediction may occur to classify these conditions as either.[4]

DISCUSSION

Generally, all four neural network models succeeded in accomplishing the task assigned to assist diagnosis of the musculoskeletal compartment.

A major medical problem is correctly identifying the patient's illness when several clinical conditions are present. The CSAE neural network can reliably distinguish the form of articular bone in ultrasound images with high sensitivity. Shape abnormalities are quantified to determine the etiology of the disease. The current network is limited to identifying rheumatoid arthritis, psoriatic arthritis, and healthy control. Presenting the model with the undefined condition would lead to automated clustering into the closest match of the three categories. Nevertheless, the improved model version is expected to contribute to disease classification when classical biomarkers are absent. Several models for joint localization have been proposed for imaging analysis. However, the *local label smoothing* CNN model uses a simple pipeline, utilizing a single machine learning model. This implies that neural network models are continuously being developed to find the most effective framework to produce the same impact.

Training DeepResolve to replicate high-resolution features was successful. However, the reconstruction of coronal and axial images appears blurry and over smoothed due to the resolving pattern following the slice direction (left to right). Limitations of the ability lie in the learning input; image reconstruction depends on the taught pattern/ direction. Nonetheless, patch edges do little to no effect on image reconstruction ability. The DeepResolve reconstruction tool is expected to facilitate radiologists in pinpointing the sources of disorders accurately. On the contrary, the risk factor prediction model for knee osteoarthritis suggests the potential of a nonimage method. The algorithm learns from previous patients' data compared to control groups. Trends and tendencies are analyzed to predict future risks and progression. However, due to the data obtained for testing, the current Deep-KOA model needs to include information on several variables, such as KOA grading, laboratory results, pathologic characteristics, genetic parameters, and other variables which might contribute to the prediction. Despite the limitations, the model could be clinically implemented, adding more information to support deep learning in the algorithm.

Likewise, both image and nonimage approaches complement a life-long treatment plan. The nonimage method enables physicians to aid high-risk patients using a prevention approach based on their EMR rather than the conventional biomechanical and imaging screening. Accurate imaging helps medical workers understand patients' conditions accurately to prescribe adequate medication with minimal side effects. This also contributes to the World Health Organization's global rehabilitation agenda. Health institutions could allocate resources for preventive treatments to demographics with higher risk. Furthermore, regarding financial matters, this method is cheaper when applied on a larger scale. Thus, it is affordable to the healthcare system for lower economic class citizens living in developing countries.

CONCLUSIONS

The use of deep learning has a great prospect of assisting patients with musculoskeletal diseases. Artificial intelligence in the medical field aids early prevention and diagnosis by improving efficiency, imaging quality, and diagnosis accuracy. This aligns with the global rehabilitation agenda for a life-long treatment plan. Cost-effective and efficient technologies provide a positive outlook for healthcare programs. Integrating a multidisciplinary approach between medicine and computer science might be the key to developing a precise patient-centric intervention system.

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